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Ranking general circulation models for India using TOPSIS

K. Srinivasa Raju and D. Nagesh Kumar

ABSTRACT

Eleven general circulation models/global climate models (GCMs) – BCCR-BCCM2.0, INGV-ECHAM4, GFDL2.0, GFDL2.1, GISS, IPSL-CM4, MIROC3, MRI-CGCM2, NCAR-PCMI, UKMO-HADCM3 and UKMO-HADGEM1 – are evaluated for Indian climate conditions using the performance indicator, skill score (SS). Two climate variables, temperature *T* (at three levels, i.e. 500, 700, 850 mb) and precipitation rate (Pr) are considered resulting in four SS-based evaluation criteria (T500, T700, T850, Pr). The multicriterion decision-making method, technique for order preference by similarity to an ideal solution, is applied to rank 11 GCMs. Efforts are made to rank GCMs for the Upper Malaprabha catchment and two river basins, namely, Krishna and Mahanadi (covered by 17 and 15 grids of size $2.5^\circ \times 2.5^\circ$, respectively). Similar efforts are also made for India (covered by 73 grid points of size $2.5^\circ \times 2.5^\circ$) for which an ensemble of GFDL2.0, INGV-ECHAM4, UKMO-HADCM3, MIROC3, BCCR-BCCM2.0 and GFDL2.1 is found to be suitable. It is concluded that the proposed methodology can be applied to similar situations with ease.

Key words | general circulation models, India, rank, skill score, TOPSIS

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INTRODUCTION

General circulation models/global climate models (GCMs) are three-dimensional mathematical models based on principles of fluid dynamics, thermodynamics and radiative heat transfer. These are easily capable of simulating/forecasting present/future values of various climatic parameters. Output of GCMs can be used as the basis to analyze impacts on hydrologic systems (Smith & Chiew 2010). However, uncertainties in developing and applying GCMs, initial condition, boundary condition, model structure and emission scenarios significantly affect their output (Wilby & Harris 2006). These necessitate selection of a suitable GCM/ensemble of GCMs (as sometimes no single model is found to be uniformly superior) so that downscaling of various parameters can be explored with confidence for adaptation at regional/local level for drinking water supply, irrigation, floods and droughts situations. Anandhi *et al.* (2011) discussed three general approaches for selecting GCMs: namely, use all available GCMs and use the multi-model ensemble mean or choose a subset of GCMs. They also cautioned that 'neither good performance across an arbitrary suite of measures of observed climate, nor agreement in output across a collection of models, provides a rigorous basis for assessing the accuracy of a future prediction'. Knutti *et al.* (2010) suggested suitable metric/measures to assess the performance of GCMs, whereas Guilyardi *et al.* (2009) emphasized that metrics 'should be concise, physically informative, societally relevant and easy to understand, compute and compare'.

Keeping these points in view, 11 GCMs – BCCR-BCCM2.0, INGV-ECHAM4, GFDL2.0, GFDL2.1, GISS, IPSL-CM4, MIROC3, MRI-CGCM2, NCAR-PCMI, UKMO-HADCM3 and UKMO-HADGEM1 – are chosen from the CMIP3 data base. There is no specific basis for choosing two GFDL variations and only NCAR-PCMI. However, the two variations of GFDL are considered in order to study how they respond to the chosen problem. Necessary data for these models over India have been extracted from the IPCC data distribution center website.

Chosen GCMs are evaluated for: (a) Upper Malaprabha catchment, Karnataka, India; (b) two Indian river basins,

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Krishna and Mahanadi, covered by 17 and 15 grids of size $2.5^\circ \times 2.5^\circ$, respectively; and (c) India (covered by 73 grids of size $2.5^\circ \times 2.5^\circ$) using the performance indicator, skill score (SS) for the climate variable, temperature (three levels, i.e. 500, 700, 850 mb and referred from now as T500, T700, T850) and precipitation rate (Pr). The multi-criterion decision-making method (MCDM), technique for order preference by similarity to an ideal solution (TOPSIS), is used to rank the GCMs. Table 1 presents information about the GCMs used in the study. For convenience, only the acronyms mentioned in column 4 are used further.

LITERATURE REVIEW

Different researchers used various metrics for evaluating GCMs which are explained in brief.

Table 1 | Details of GCMs considered and their acronyms

S. No. (1)	GCM (2)	Organisation (3)	Acronym (4)
1	BCCR-BCCM 2.0	Bjerknes Centre for Climate Research, Norway	BCCR
2	INGV-ECHAM 4	Istituto Nazionale Di Geofisica E Vulcanologia, Italy	ECHAM
3	GFDL2.0	Geophysical Fluid Dynamic Laboratory, USA	GFDL2.0
4	GFDL2.1	Geophysical Fluid Dynamic Laboratory, USA	GFDL2.1
5	GISS	Goddard Institute for Space Studies, USA	GISS
6	IPSL-CM 4	Institut Pierre Simon Laplace, France	IPSL
7	MIROC3	Centre for Climate Research, Japan	MIROC3
8	MRI-CGCM2	Meteorological Research Institute, Japan	CGCM2
9	NCAR-PCMI	Parallel Climate Models, NCAR, USA	PCMI
10	UKMO-HADCM3	UK Met Office, UK	HADCM3
11	UKMO-HADGEM1	UK Met Office, UK	HADGEM1

Perkins *et al.* (2007) assessed 14 GCMs for daily minimum and maximum temperatures and daily rainfall for 12 regions of Australia. The evaluation was based on SS. GCMs were ranked based on each variable SS as well as on average SS. Similar studies were reported in Suppiah *et al.* (2007), Maximo *et al.* (2008), Perkins *et al.* (2009, 2013) and Perkins & Pitman (2009). Model climate performance index and model variability index were developed by Gleckler *et al.* (2008) for evaluating GCMs. GCM evaluation aspects are also discussed in detail in Mujumdar & Ghosh (2008), Pierce *et al.* (2009), Macadam *et al.* (2010), Fordham *et al.* (2011) and Johnson *et al.* (2011). Intercomparison of GCMs for hydrologic predictability are discussed by Reshmi Devi & Nagesh Kumar (2010). Johnson & Sharma (2009) and Ojha *et al.* (2014) applied the variable convergence score method, respectively, for case studies of Australia and India which is used to rank climatic variables based on coefficient of variation of an ensemble of GCMs. Both studies concluded that there is no single widely acceptable metric for assessing climate models. Fu *et al.* (2013) applied a multicriteria score-based method to assess GCM performance at the regional scale over the southeastern Australia region. Monthly mean sea level pressure, monthly air temperature, monthly and annual rainfall are considered for evaluation of 25 GCMs. They also compared the CMIP5 and CMIP3 based GCMs. It is concluded that results can be used for better regional climate change impact analysis. Su *et al.* (2013) evaluated performance of 24 GCMs in CMIP5 environment over the eastern Tibetan Plateau by comparing the model outputs with ground observations for precipitation and temperature. It is observed that most GCMs reasonably capture the climatological patterns and spatial variations of the observed climate for temperature. Hughes *et al.* (2014) assessed the skill of nine GCMs for 15 catchments in five regions of South Africa with the objective of testing whether GCMs are able to reproduce precipitation distribution statistics and patterns of seasonality, persistence and extremes. Differences in the GCMs' skill across the different regions and in the skill ranking between coastal areas and inland regions are observed. Grose *et al.* (2014) assessed a set of 27 GCMs from the CMIP5 ensemble for their performance for the western tropical Pacific and differences from CMIP3. It is concluded that careful interpretation and consideration of biases is required when using CMIP5 outputs for generating regional climate projections.

Limitations of the above-mentioned studies are as follows:

- The SS approach was not used for assessing suitability of GCMs and adaptability for Indian climate conditions.
- No study has used the MCDM process where all criteria are simultaneously considered for ranking GCMs.

The objectives of the present study, addressing the above limitations, are summarized below:

- To analyze the capability of chosen GCMs to simulate monthly precipitation and temperature (at three levels) using a probability based SS.
- To develop a methodology for ranking GCMs that can be used as the basis for hydrological modelling applications.
- To evaluate the suitability of GCMs for Indian conditions.

STUDY AREA

Upper Malaprabha catchment

Upper Malaprabha catchment, Karnataka State, India is located between latitudes 15°00′ and 16°12′ N and longitudes 74°14′ and 76°05′ E. The catchment area of the river up to the dam site is 2,564 km^2. The area of the reservoir at full reservoir level is 13,578 ha. The reservoir has live storage capacity of 870 Mm^3. The mean annual rainfall in the command area is 576 mm. Figure 1 presents a location map of the Malaprabha reservoir. There are two main canals in this project. The left bank canal serves a command area of 53,137 ha and the right bank canal serves 128,634 ha.

Krishna and Mahanadi river basins

Figure 1 also presents a location map of the Krishna and Mahanadi river basins. Krishna basin lies between latitude 13°07′ and 19°25′ N and longitude 73°21′ and 81°09′ E. The

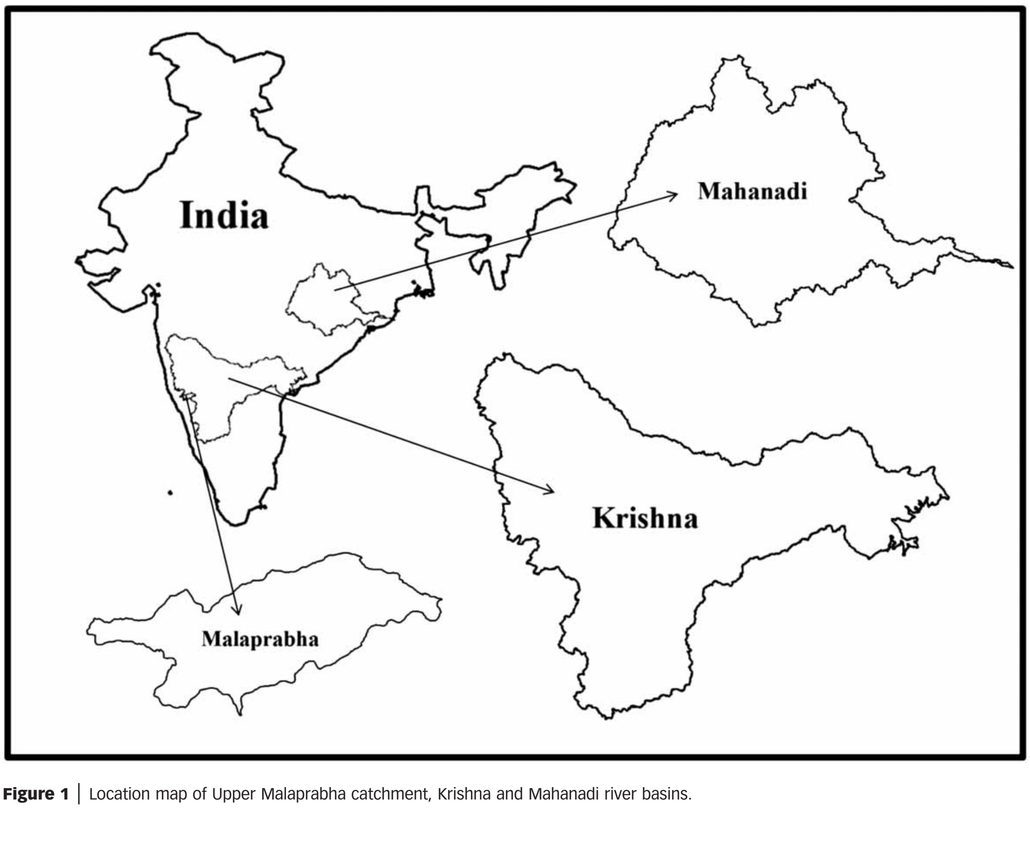

Figure 1 | Location map of Upper Malaprabha catchment, Krishna and Mahanadi river basins.

river rises in the western ghats at an altitude of 1,337 m just north of Mahabaleshwar, about 64 km from the Arabian Sea. The catchment area is 258,948 km^2 spread over the states of Maharashtra (26.8%), Karnataka (43.7%) and Andhra Pradesh (29.5%). Mahanadi basin lies between latitude 19°20′ and 23°35′ N and longitude 80°30′ and 86°50′ E. The catchment area is 141,600 km^2 spread over the states of Chhattisgarh, Orissa, Madhya Pradesh, Jharkhand and Maharashtra, of which more than 99% is in Chhattisgarh and Orissa.

India

India lies between longitudes 68°7′ and 97°25′ E and latitudes 8°4′ and 37°6′ N. The average annual rainfall is 125 cm, but with significant spatial variations. In addition, there is significant regional and temporal variation in the rainfall distribution. Around 80% of the annual rainfall is received in the four rainy months of June to September.

SS AND ANALYSIS

SS (Perkins *et al.* 2007) measures the similarity between two probability density functions (PDFs) related to GCM-based simulation and observation. It measures the amount of overlap between GCM-based PDF and observed PDF. The SS approach estimates the cumulative minimum value of GCM-based and observation-based distributions of each binned value. This results in the measurement of the common area between the two PDFs expressed as the SS. If a model simulates the observed conditions perfectly, the SS will be one, which is the total sum of the binned values in the given PDFs. If a model simulates the observed PDF poorly, the SS will be close to zero (Maximo *et al.* 2008; Anandhi *et al.* 2011). SS is expressed as

$$SS = \sum_{i=1}^{nb} \min(f_m, f_o) \tag{1}$$

where f_m and f_o are the frequency of values in the given bin from the chosen GCM and observed data; nb is number of bins used to calculate the PDF for a given region.

DESCRIPTION OF TOPSIS

TOPSIS is based on the principle that the chosen alternative should have the shortest distance from the ideal solution and furthest distance from the anti-ideal solution (Chen & Hwang 1992; Opricovic & Tzeng 2004; Raju & Nagesh Kumar 2010). The methodology of TOPSIS consists of the following:

1. Computation of separation measure D_a^+ of each alternative a from the ideal solution, that is, Euclidean distance of each criterion from its ideal value, and summing these for all criteria $(j = 1, 2, \ldots. J)$ for given alternative a, that is,

$$D_a^+ = \sqrt{\sum_{j=1}^{J} (w_j f_j(a) - w_j f_j*)^2} \tag{2}$$

   where $j = 1, 2, \ldots J$; $f_j(a)$ = normalized value of criterion j for alternative a; f_j* = normalized ideal value of criterion j; w_j = weight assigned to the criterion j.
2. Computation of separation measure D_a^- of each alternative a from the anti-ideal solution, that is, Euclidean distance of each criterion from its anti-ideal value, and summing these for all criteria $(j = 1, 2, \ldots. J)$ for given alternative a, that is,

$$D_a^- = \sqrt{\sum_{j=1}^{J} (w_j f_j(a) - w_j f_j^{**})^2} \tag{3}$$

   where f_j^{**} = normalized anti-ideal value of criterion j.
3. Computation of relative closeness C_a of each alternative a is

$$C_a = \frac{D_a^-}{(D_a^- + D_a^+)} \tag{4}$$

The alternatives are ranked based on the C_a values. The higher the C_a value, the better the alternative. Figure 2 presents a flow chart of the present methodology.

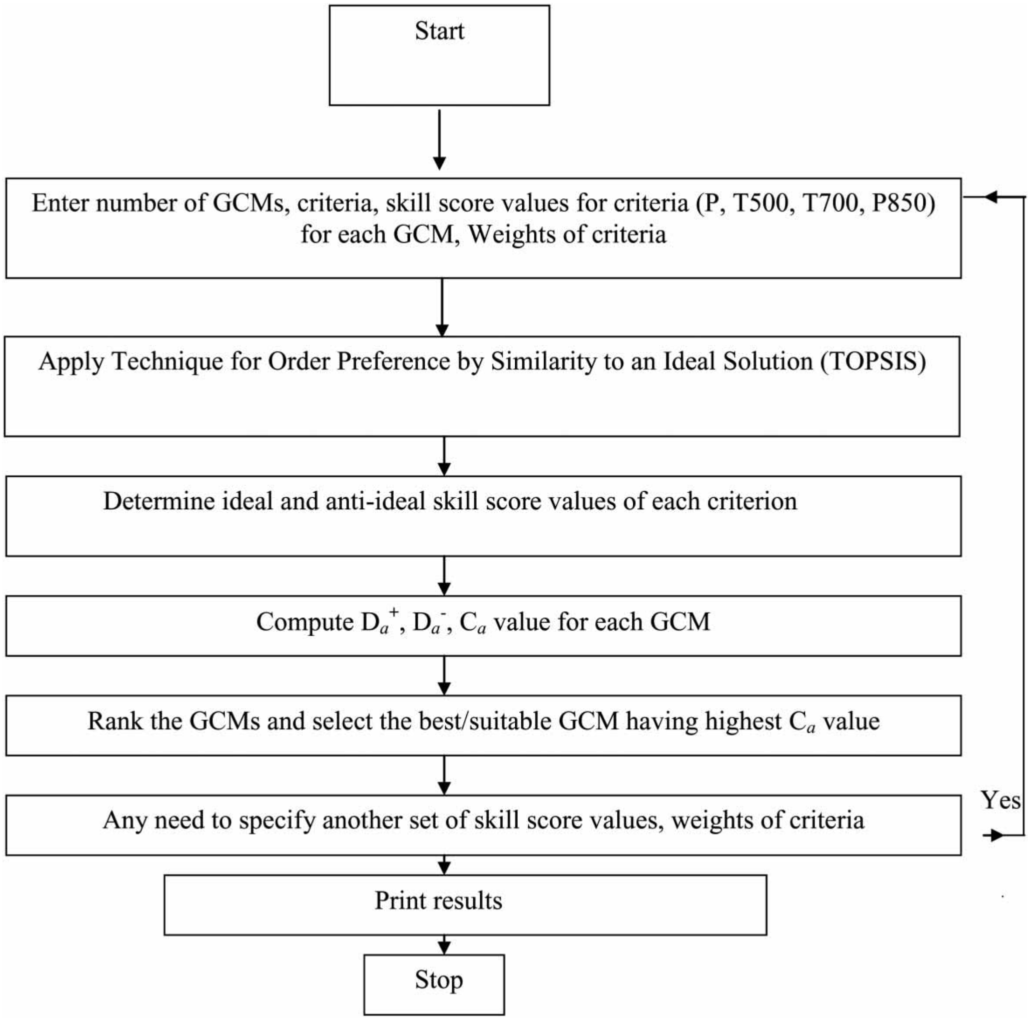

Figure 2 | Flow chart of the proposed methodology.

RESULTS AND DISCUSSION

Case study of Upper Malaprabha catchment

Six hundred data sets grid wise relating to the period 1950–1999 (12 per year for 50 years) obtained from NCEP-NCAR reanalysis environment are compared with historical runs obtained from each of the 11 GCMs to assess the SS. Interactive code is developed for computation of the SS (grid wise) for the climate variable, temperature (° Kelvin) and precipitation (kg/m^2/s). In the case of precipitation, 30 bins ($nb = 30$) each of size 0.0000157 kg/m^2/s are employed whereas 58 bins each of size 5° Kelvin are used for temperature (Maximo *et al.* 2008). Frequencies of values within each bin are then calculated for observed data (f_o) and general circulation model output (f_m) based on which SS is computed for T500, T700, T850, and P (Equation (1)).

SS values for Upper Malaprabha catchment for Pr, T500, T700, T850 are presented in Table 2 (columns 2, 3, 4, 5) and Figure 3. It is observed from Table 2 that for precipitation the minimum SS is 0.6283 for PCMI whereas the maximum is 0.8567 for MIROC3 (column 2); for T500, minimum and maximum SSs are 0.2833 and 0.5533 for GISS/IPSL and GFDL2.0/GFDL2.1/BCCR (column 3); for T700, minimum and maximum SSs are 0.1783 and 0.4100 for PCMI and HADCM3 (column 4); and for T850,

Table 2 | SS values and outcome of TOPSIS for the chosen 11 GCMs for Upper Malaprabha catchment

	SS values related to climatic variables				Outcome of TOPSIS			
GCM (1)	Pr (2)	T500 (3)	T700 (4)	T850 (5)	Da^+ (6)	Da^- (7)	C_a (8)	Rank (9)
BCCR	0.7717	0.5533	0.2583	0.3300	0.2796	0.2595	0.4814	6
ECHAM	0.6833	0.3483	0.2800	0.3917	0.2972	0.2264	0.4324	8
GFDL2.0	0.8150	0.5533	0.4000	0.4183	0.2414	0.2856	0.5420	1
GFDL2.1	0.8350	0.5533	0.2633	0.3783	0.2688	0.2757	0.5063	2
GISS	0.7783	0.2833	0.2033	0.3150	0.3228	0.2273	0.4132	9
IPSL	0.6583	0.2833	0.2017	0.4167	0.3170	0.2133	0.4022	10
MIROC3	0.8567	0.3583	0.3867	0.3800	0.2730	0.2688	0.4961	3
CGCM2	0.7550	0.4517	0.2367	0.5250	0.2703	0.2629	0.4931	5
PCMI	0.6283	0.3217	0.1783	0.3367	0.3272	0.2005	0.3800	11
HADCM3	0.8100	0.3483	0.4100	0.4100	0.2689	0.2638	0.4952	4
HADGEM1	0.7883	0.2850	0.2067	0.3983	0.3110	0.2377	0.4332	7

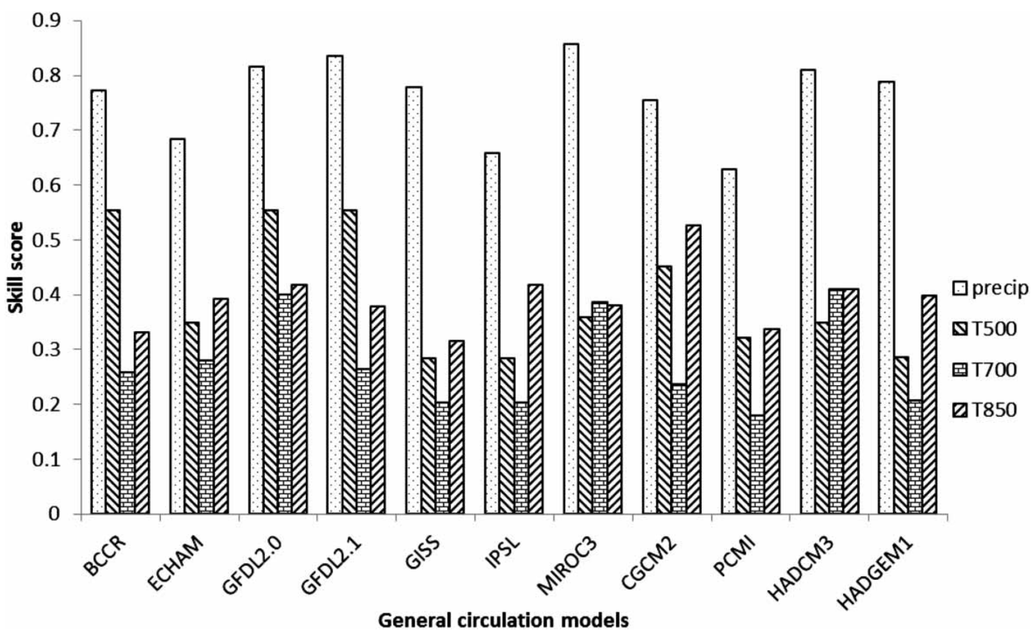

Figure 3 | SS related to various GCMs for Upper Malaprabha catchment.

minimum and maximum SSs are 0.315 and 0.525 for GISS and CGCM2 (column 5). The above analysis indicates that ranking is different for each GCM with reference to each criterion. It is also observed that MIROC3, GFDL2.0/GFDL2.1/BCCR, HADCM3, CGCM2 occupy the first position (due to their higher SSs). SSs (columns 2, 3, 4, 5) for each GCM for Pr, T500, T700, T850 are the inputs to the MCDM method TOPSIS.

Equal weights of 0.25 are considered for each criterion, Pr, T500, T700, T850 for TOPSIS analysis. In TOPSIS, the ideal value is assigned as one (higher SS is desirable), and the anti-ideal value is assigned as zero (lowest SS) while the optimal value is the ideal value. The outputs from TOPSIS are D_a^+ (Equation (2)), D_a^- (Equation (3)), C_a (Equation (4)) and corresponding ranking pattern (Raju & Nagesh Kumar 2010). D_a^+ (column 6), D_a^- (column 7) and C_a (column 8) for the 11 chosen GCMs are presented in Table 2 along with ranking pattern (column 9). GFDL2.0, GFDL2.1, MIROC3 occupied the first three positions (with C_a values of 0.5420, 0.5063, and 0.4961) and IPSL, PCMI occupied last two positions with C_a values of 0.4022 and 0.3800. It is suggested that an ensemble of GFDL2.0, GFDL2.1 and MIROC3 is suitable for the Upper Malaprabha catchment. Ensemble mean can be used for downscaling precipitation and temperature. A sample calculation for using TOPSIS is presented in the Appendix (available online at http://www.iwaponline.com/jwc/006/074.pdf).

Case study of river basins

The suitability of GCMs for the two river basins, Krishna and Mahanadi in India, is also evaluated. Table 3 presents the latitude and longitude (*Integrated Hydrological Data Book* 2012) along with number of grid points covered by each basin. The suitability of GCMs in terms of the first and second ranks is presented in columns 4 and 5 of Table 3. The GCMs that occupied the first three ranks in the average ranking perspective, which allows a consensus to be reached (Bui 1987), are also presented in column 6. GCMs that occupy (a) the first three ranks in the average ranking perspective and (b) the first and second ranks in more than two grid points among the relevant grid points are considered for evolving a suitable ensemble and are shown in column 7. Some salient features which are the outcome of the present study are presented below for each basin.

Krishna river basin

- GFDL2.0, MIROC3 and GFDL2.1 attained the first three ranks (based on average ranking of 17 grids) as shown in column 6.
- First rank was attained by GFDL2.0, GFDL2.1, GISS, MIROC3, CGCM2 in 9, 1, 1, 5, 1 grid points, respectively. It is also observed that GFDL2.0 and MIROC3 occupied 82.35% of 17 grids.
- BCCR, GFDL2.0, GFDL2.1, MIROC3, CGCM2 attained second rank in 3, 5, 5, 2, 2 grid points, respectively. It is also observed that GFDL2.0 and GFDL2.1 occupied 58.82% of 17 grids.
- Hence, the ensemble of GFDL2.0, MIROC3, GFDL2.1 and BCCR is suggested for Krishna river basin.

Mahanadi river basin

- GFDL2.1, MIROC3 and CGCM2 attained the first three ranks (based on average ranking of 15 grids).
- BCCR, ECHAM, GFDL2.0, GFDL2.1, IPSL, MIROC3, CGCM2, PCMI, HADGEM1 attained the first rank in 1, 1, 1, 1, 1, 4, 2, 2, 2 grid points, respectively. It is also observed that MIROC3, CGCM2, PCMI and HADGEM1 occupied 66.67% (out of 15).
- BCCR, GFDL2.0, GFDL2.1, MIROC3, CGCM2, PCMI, HADCM3, HADGEM1 attained the second rank in 1, 1, 3, 2, 1, 3, 1, 3 grid points, respectively. It is also

Table 3 | Suitability of GCMs for the Krishna and Mahanadi river basins

River basin (1)	Latitude and longitude (2)	Number of grid points covered (3)	Suitability of GCMs (first rank) (4)	Suitability of GCMs (second rank) (5)	First three ranks in average ranking perspective (6)	Suggested ensemble (7)
Krishna	13°07′ N to 19°25′N; 73°21′ E to 81°09′ E	~17	GFDL2.0 (9) MIROC3 (5)	BCCR (3), GFDL2.0 (5), GFDL2.1 (5)	GFDL2.0, MIROC3, GFDL2.1	GFDL2.0, MIROC3, GFDL2.1, BCCR
Mahanadi	19°20′ N to 23°35′ N; 80°30′ E to 86°50′ E	~15	MIROC3 (4)	GFDL2.1 (3), PCMI (3), HADGEM1 (3)	GFDL2.1, MIROC3, CGCM2	MIROC3, GFDL2.1, CGCM2, PCMI, HADGEM1

Note: GCMs appearing in two grid points in first and second rank positions are not presented here and not considered for the ensemble; values in parentheses represent the number of grid points in which GCMs appears.

observed that GFDL2.1, MIROC3, PCMI and HADGEM1 occupied 73.33% out of 15.

- Hence, the ensemble of MIROC3, GFDL2.1, CGCM2, PCMI and HADGEM1 is suggested for the Mahanadi river basin.

Case study of India

For this purpose, 73 grid points ($2.5^\circ \times 2.5^\circ$) covering India are identified and the corresponding 73 payoff matrices are evolved. A similar process of application of TOPSIS as performed for the Upper Malaprabha catchment is repeated for 73 grid points for India and an analysis of the results is presented in Table 4. It is observed from Table 4 that GFDL2.0, ECHAM, HADCM3 and MIROC3 attained first rank in 19, 11, 11, 10 grid points, respectively (69.9%), whereas GFDL2.0, GFDL2.1, BCCR and ECHAM attained second rank in 13, 13, 13, 11 grid points, respectively (68.5%). In the first rank scenarios, GFDL2.0 and (ECHAM, HADCM3) occupied 19 and 11 grid points whereas in second rank scenarios (GFDL2.0, GFDL2.1, BCCR) and ECHAM occupied 13 and 11 grid points. Third rank is attained by BCCR, GFDL2.1, in 19 and 13 grid points. It is interesting to note that MIROC3 never attained 10th rank whereas BCCR, GFDL2.0, CGCM2 never attained 11th rank. Table 5 presents spatial distribution of GCMs for the first rank. It is observed from Table 4 that GFDL2.0 occupied the first position in 19 grid points whereas GFDL2.1 occupied first position in four grid points contributing 23 out of 73 grid points; for second position, these two together contribute 26 grid points out of 73. Figures 4(a) and 4(b) present the number of grid points in which GCMs attained particular ranks. Numbers 1 to 11 shown in the legend represent the ranking pattern. It is also observed that for 17.5° latitude and 75°, 77.5°, 80° longitude, GFDL2.0 is preferred whereas for 20° latitude and 75°, 77.5°, 80° longitude, MIROC3 is preferred. Similar types of inference were drawn for various combinations of latitude and longitudes.

The average ranking method (Bui 1987) is employed to aggregate the ranking related to 73 grid points of India for each GCM employed to arrive at a consensus. It is noted that BCCR, GFDL2.0 and GFDL2.1 attained first three ranks whereas GISS and IPSL attained the last two ranks. It can be observed from Tables 4 and 5 that an ensemble of GCMs is to be evolved as no single GCM can be recommended for India. The GCMs which: (a) attained the first three ranks in average ranking perspective; and (b) attained the first and second ranks (in more than 10 grid points in 73 grid points covering India) are taken into consideration in formulating the ensemble. Accordingly, the ensemble of GFDL2.0, ECHAM, HADCM3, MIROC3, BCCR and GFDL2.1 is suggested for India both for precipitation rate and temperature.

Table 4 | Number of grid points among 73 in India in which GCMs have attained a particular rank using TOPSIS

	Ranking positions										
GCM	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
BCCR	7	13	19	7	7	6	2	4	3	5	0
ECHAM	11	11	4	2	3	2	6	7	3	7	17
GFDL2.0	19	13	4	5	4	5	10	5	4	4	0
GFDL2.1	4	13	13	17	11	1	2	7	1	3	1
GISS	1	0	3	5	6	8	7	9	11	7	16
IPSL	1	0	3	2	2	5	8	7	17	18	10
MIROC3	10	5	8	8	10	9	6	7	9	0	1
CGCM2	3	4	4	8	13	15	4	10	7	5	0
PCMI	2	5	1	4	9	6	8	3	6	14	15
HADCM3	11	5	11	5	3	9	12	9	3	2	3
HADGEM1	4	4	3	10	5	7	8	5	9	8	10

Table 5 | TOPSIS selected GCMs (first rank) for different grid points in India

S. No	Lat	Long	GCM	S. No	Lat	Long	GCM
1	7.5	77.5	GFDL 2.0	37	22.5	92.5	HADGEM1
2	7.5	95	BCCR	38	25	70	GFDL 2.0
3	10	77.5	GFDL 2.0	39	25	72.5	GFDL 2.1
4	10	80	BCCR	40	25	75	GFDL 2.0
5	10	92.5	GFDL 2.1	41	25	77.5	MIROC3
6	12.5	72.5	MIROC3	42	25	80	MIROC3
7	12.5	75	GFDL 2.0	43	25	82.5	BCCR
8	12.5	77.5	GFDL 2.0	44	25	85	CGCM2
9	12.5	80	GFDL 2.0	45	25	87.5	ECHAM
10	12.5	92.5	CGCM2	46	25	90	ECHAM
11	15	75	GFDL 2.0	47	25	92.5	GFDL 2.0
12	15	77.5	GFDL 2.0	48	25	95	BCCR
13	15	80	GFDL 2.0	49	27.5	70	GFDL 2.0
14	15	82.5	GFDL 2.1	50	27.5	72.5	GFDL 2.0
15	17.5	72.5	MIROC3	51	27.5	75	HADCM3
16	17.5	75	GFDL 2.0	52	27.5	77.5	HADCM3
17	17.5	77.5	GFDL 2.0	53	27.5	80	ECHAM
18	17.5	80	GFDL 2.0	54	27.5	82.5	ECHAM
19	17.5	82.5	CGCM2	55	27.5	85	ECHAM
20	17.5	85	IPSL	56	27.5	87.5	ECHAM
21	20	72.5	MIROC3	57	27.5	90	ECHAM
22	20	75	GISS	58	27.5	92.5	BCCR
23	20	77.5	MIROC3	59	27.5	95	BCCR
24	20	80	MIROC3	60	30	72.5	GFDL 2.0
25	20	82.5	MIROC3	61	30	75	HADCM3
26	20	85	PCMI	62	30	77.5	HADCM3
27	20	87.5	HADGEM1	63	30	80	ECHAM
28	22.5	70	GFDL 2.0	64	30	95	BCCR
29	22.5	72.5	GFDL 2.0	65	32.5	75	HADCM3
30	22.5	75	HADCM3	66	32.5	77.5	HADCM3
31	22.5	77.5	MIROC3	67	32.5	80	ECHAM
32	22.5	80	MIROC3	68	35	75	HADCM3
33	22.5	82.5	GFDL 2.1	69	35	77.5	HADCM3
34	22.5	85	PCMI	70	35	80	ECHAM
35	22.5	87.5	HADGEM1	71	37.5	72.5	ECHAM
36	22.5	90	HADGEM1	72	37.5	75	HADCM3
				73	37.5	77.5	HADCM3

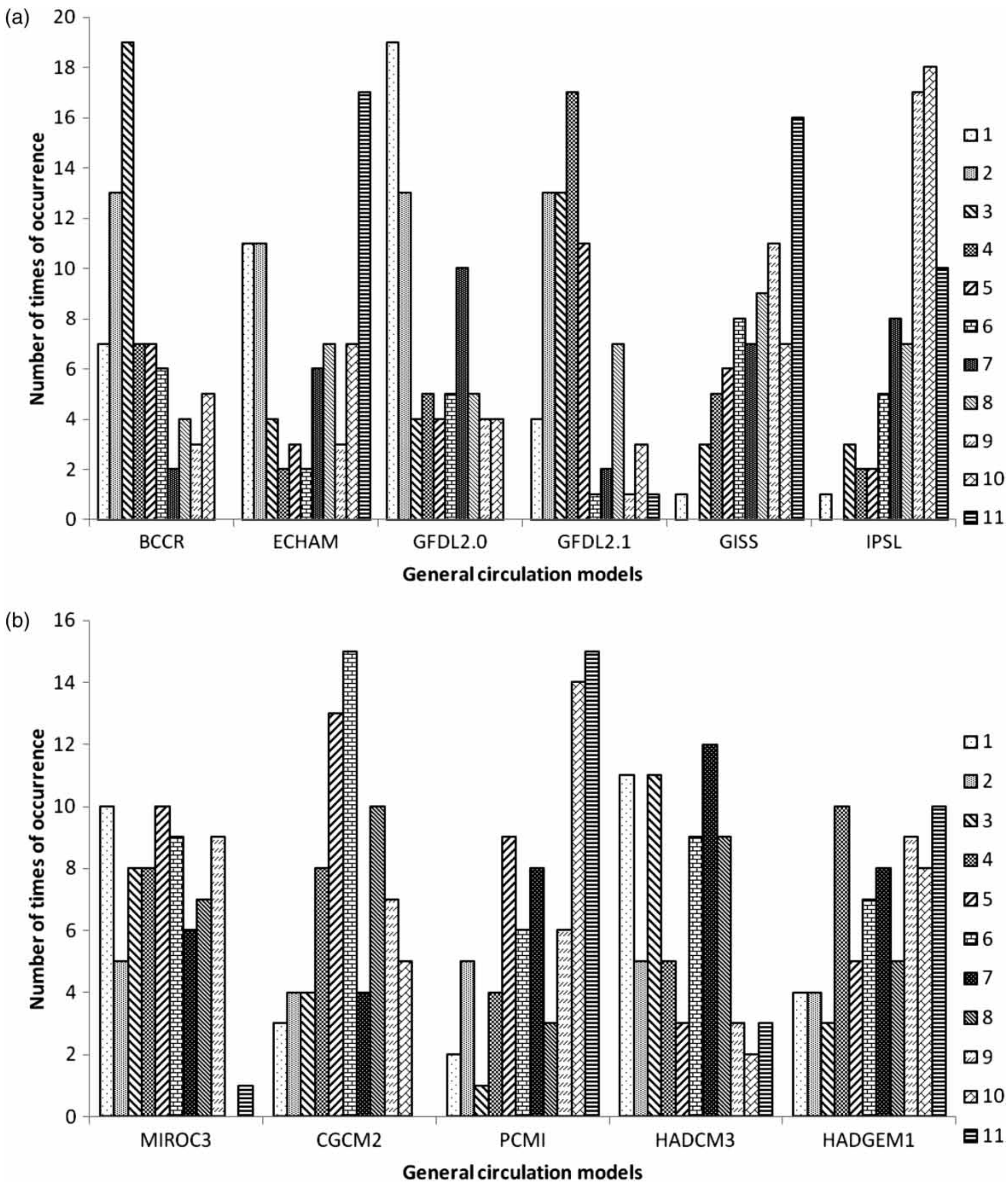

Figure 4 | Number of grid points in which GCMs attained a particular rank in case of: (a) 6 GCMs and (b) 5 GCMs.

To the authors' knowledge, this is the first application of SS methodology for ranking GCMs using the MCDM method TOPSIS in Indian conditions; that is, for one catchment, two river basins and the whole of India. In the future, CMIP5 data sets will be used for further studies with more decision making methods and more indicators in Indian conditions.

SUMMARY AND CONCLUSIONS

The SS measure is used to rank 11 GCMs – BCCR, ECHAM, GFDL2.0, GFDL2.1, GISS, IPSL, MIROC3, CGCM2, PCMI, HADCM3 and HADGEM1 – for Upper Malaprabha catchment, two river basins, Krishna and Mahanadi, and India, for precipitation rate and temperature. TOPSIS is employed to rank the 11 GCMs. Specific conclusions emanating from the present study are as follows:

1. It is observed that GFDL2.0, GFDL2.1 and MIROC3 attained first three ranks and IPSL and PCMI occupied last two positions for Upper Malaprabha catchment.
2. The ensemble of GFDL2.0, ECHAM, HADCM3, MIROC3, BCCR and GFDL2.1 is suggested for India as no single GCM is recommended.
3. The ensemble of GFDL2.0, MIROC3, GFDL2.1 and BCCR is suggested for Krishna river basin whereas MIROC3, GFDL2.1, CGCM2, PCMI and HADGEM1 is suggested for Mahanadi river basin.

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